

# Independent Component Analysis for Motion Artifacts Removal from Electrocardiogram

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## Abstract

A method of using Independent Component Analysis to remove motion induced artifacts in the signals picked up by ECG electrodes is developed in this paper. In a first aid setting, ECG electrodes on patients cannot always keep stationary, resulting in a large amount of contact noise in acquired signals. Similar problems occur in ECGs in motion, e.g. sports and ambulatory ECGs. The motion induced artifacts are known to undermine the arrhythmia recognition. An artificial neural system for automated ECG classification with an extra independent component analysis de-noising pre-processor is proposed and validated by pre-recorded real ECG and noise datasets. The proposed system shows improved recognition accuracy, providing a useful means to more accurately detect arrhythmia from ECGs in the presence of no trivial motion related noises.

## Keywords

*Independent Component Analysis; Artifact; Neural Network; Classification; Electrocardiogram; Noise; Recognition*

## Introduction

Electrocardiogram (ECG), a noninvasive method to observe and monitor the electrical activity of the heart over a period of time, provides useful insights into the irregularity and pattern of heartbeats and thus helping with the diagnosis of many cardiac diseases. Early diagnosis, timely treatment and long term monitoring are known to prevent unexpected heart attacks and heart failures. Automated ECG pattern recognition has been broadly studied over the past few decades, accumulating a large number of effective algorithms and numerous publications. These have enabled long term monitoring and fast diagnosis without an experienced cardiac specialist on site. ECG monitoring is sometimes used outside clinical environment in a first aid setting for example. Due to motions of anxious patients, associated artifacts found in ECG signals are severer than those taken in hospitals or other clinical environments. Round the clock Holter ECG monitoring and recording, other ambulatory ECGs,

and sports ECGs, just to name a few, are all prone to high levels of motion related noise. Certain low cost minimum profile setups are more likely to have compromised signal to noise ratios, which makes the so-acquired ECG signals more difficult to process by automated ECG patterns recognition and diagnosis systems.

The ECG is often contaminated by noise and artifacts. ECG contaminants can be classified as (Clifford et al., 2006): Power line mains interference, 50  $\pm$  0.2 Hz mains noise (or 60 Hz in some countries); Electrode contact noise, which is the interference resulting from the intermittent loss of contact between the electrode and skin; Patient-electrode motion artifacts, occurring due to movement of the electrode away from the contact area on the skin. Last but not least, Electromyography (EMG) signals often appear to be a non-trivial source of contamination in ECG and especially ambulatory ECG signals. Although each of these contaminants may be reduced by careful selection of hardware and experimental setup, it is impossible to completely eliminate them.

The applications of Independent Component Analysis (ICA) and Blind Source Separation (BSS) to ECG and other biomedical signal processing are a relatively new but rapidly expanding area of study. The potential of blind signal separation to extract extra information about the heart and body has been explored (Owis et al., 2002). Independent component analysis has been found useful in revealing hidden factors of biomedical signals (Chou and Yu, 2008; James and Hesse, 2005; Nazmy et al., 2010; Yu and Chou, 2007). The classification of ECG is a slightly different scenario. It intends to identify diverse cardiovascular conditions and diagnose associated diseases. Some algorithms are designed to classify different types of irregularity in heart beats, e.g. normal and abnormal heart beats such as atrial fibrillation (AF), Premature Ventricular contraction (PVC) and tachycardia. Others are for the

diagnosis of various cardiovascular diseases such as myocardial infarction (MI), right and left bundle branch block. Clean ECG signals are desirable to ensure the accuracy in pattern recognition and diagnosis. Effective de-noising is often a key to achieving high accuracy and good reliability.

Motion related artifacts and EMG interferences are generally considered the most troublesome noise, since they can mimic the appearance of ectopic beats and therefore it cannot be removed by straightforward filtering (Goldberger et al., 2000; Moody et al., 1984). In this study, the ICA is proposed to exploit to separate out the motion related artifacts blended within the ECG signals utilizing the independent statistical features of the ECG signals and motion related noise, then a typical artificial neural network (ANN) classifier is adopted to work on the “cleaned” ECGs to categorize them into normal and abnormal patterns.

### Background of Electrocardiogram

ECG is a measurement of the total sum of electrical activity generated by the heart and measured from the surface of the body. In simpler terms, it is an electrical record of heart activities. It remains one of the most valuable diagnostic tools for the identification of a wide variety of cardiac arrhythmias. The ECG is measured by placing electrodes on the body surface at various prescribed locations and connecting the electrodes in different configurations to voltage amplifiers and a recorder. As a basic configuration, the “three-lead ECG” is the most common among many other possible configurations based on Einthoven triangle (Malmivuo and Plonsey, 1995) and uses only three leads for measurements to give a general profile of electrical activities of the heart.

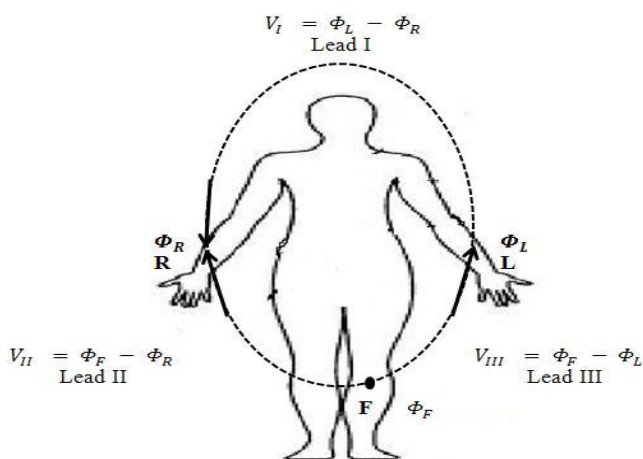


FIG.1 EINTHOVEN THREE LIMB LEADS METHOD

The Einthoven limb leads (standard leads) are defined

as follows:

$$\begin{aligned} \text{Lead I: } V_I &= \Phi_L - \Phi_R \\ \text{Lead II: } V_{II} &= \Phi_F - \Phi_R \\ \text{Lead III: } V_{III} &= \Phi_F - \Phi_L \end{aligned} \quad (1)$$

where  $\Phi$  refers to potential of that lead. in Volts. R, L and F refer to Right arm, Left Arm and Left Leg respectively. According to Kirchhoff's law, these lead voltages have the following relationship:

$$V_I + V_{III} = V_{II} \quad (2)$$

As the electrode in left leg act as ground and the potential difference of other two electrode are measured in reference with ground electrode, hence only two of these three leads are independent. The two-lead ECG configuration is routinely used in the Holter monitoring that enables the recording of the heart activity of a subject continuously over a long time with portable devices (Ye et al., 2010)

We used data from lead II obtained from MIT-BIH (Goldberger et al., 2000; Moody et al., 1984). The source of the ECGs included in the MIT-BIH Arrhythmia Database is a set of over 4000 long-term Holter recordings that were obtained from the Beth Israel Hospital. It is widely used as a benchmark or reference dataset in ECG analysis and pattern recognition work (Belgacem et al., 2003; Chou and Yu, 2008; Jiang et al., 2006; Moody et al., 2001; Wang et al., 2012).

Due to body movements, ECG signals are contaminated or even corrupted by motion artifacts also known as ‘em artifacts’. To improve the robustness of pattern recognition and classification of ambulatory ECGs, elimination of these ‘em artifacts’ is the key. An extra electrode is proposed to be placed on body where ECG is minimal, thus the signals from ECG lead II will have a part of noise,  $N'$  (which is a linearly attenuated version of the motion related noise source  $N$ ) and the signals from the extra lead, where ECG is minimal, will contain mostly the noise  $N''$ . Since noise appears in both leads that are homogeneous, all resulting from motions, the signals from the two leads are representation of the ECG and the noise with different mixing ratios. The ICA can be used to separate out the pure ECG and the motion related noise.

### Independent Component Analysis

Independent component analysis is a statistical method that is used to identify underlying factors or components that are statistically independent (Hyvärinen and Oja, 2000). The attractive feature of the ICA is that it is able to statistically separate out individual sources from their mixtures without prior information about the sources and the mixing

parameters. Cocktail party problem as illustrated in Fig 2 is a classic example to explain the ICA based BSS. Two different talker are heard by two listeners (or picked up by two microphones), due to distance discrepancy, each listener hears a different linear mixture of the sources.

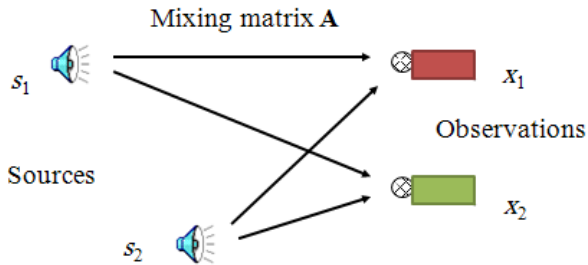


FIG. 2 COCKTAIL PARTY PROBLEM

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \quad (3)$$

where vector  $\mathbf{x}(t)$  represents the signals received,  $\mathbf{s}(t)$  the original source signals, and  $\mathbf{A}$  the mixing matrix. The objective is to separate the individual voices from the linear mixture. Given the conditions of same number of sources as there are receivers.

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) \quad (4)$$

$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) \quad (5)$$

where  $x_1$  and  $x_2$  are the signals received by the microphone, the presence of sources  $s_1$  and  $s_2$  in  $x_1$  and  $x_2$  is determined by the mixing parameters  $a_{11}, a_{12}, a_{21}$  and  $a_{22}$ . We have to separate individual sources from the mixture, with no information about the sources and mixing parameters available.

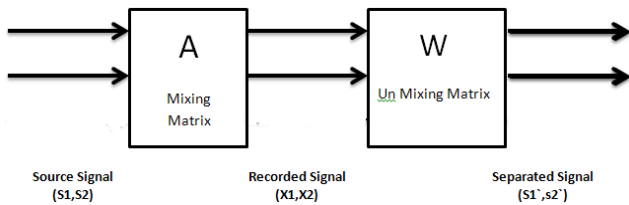


FIG. 3 ICA BLOCK DIAGRAM

Linear ICA has two prerequisites,

- 1) The measured signals are linear combinations of independent source signals.
- 2) The independent signals are non Gaussian.

Mathematically, the objective is to find unmixing or demixing matrix  $\mathbf{W}$ , which is inverse of  $\mathbf{A}$  (mixing matrix) so that we can get source signal separated.

$$\mathbf{s}(t) = \mathbf{W}\mathbf{x}(t) \quad (6)$$

The mixing and demixing process can be described as a change of coordinates, which is achieved by rotation. For example, if the sources  $S_j$  is considered as a component of vector  $\mathbf{S}$  with respect to an orthogonal basis, the observation  $X_j$  could be the component of

the very same vector in terms of a different basis. The demixing matrix thus helps find the sources  $\mathbf{s}$ .

In the current study of ECG de-noising application, we started with Centering the ECG data by subtracting mean vector  $\mathbf{m} = E\{\mathbf{x}\}$  from  $\mathbf{x}$  and then whitening was applied prior to the application of ICA algorithm. whitening transform vector  $\mathbf{x}$  to new vector  $\tilde{\mathbf{x}}$  whose components are uncorrelated and their variances equal unity. In other words, the covariance matrix of  $\tilde{\mathbf{x}}$  equals the identity matrix, which makes the covariance matrix diagonal and its components of unit variance. The ICA is usually performed by formulating an objective function, e.g. mutual information or negentropy, and then minimizing or sometimes maximizing it. This transforms the ICA problem to a numerical optimization problem (He et al., 2006). There are a number of algorithms for the ICA. In this study, a fixed-point algorithm with a nonlinear function  $g(u) = \tanh(u)$  was adopted to estimate the independent components (Hyvärinen, 1999). FastICA is one of the popular ICA techniques (Hyvärinen and Oja, 1997) and available as a freely downloadable set of Matlab functions from the Internet (FastICA). FastICA attempts to separate underlying sources from the given measurement set based on their 'non-Gaussianity'. The basic principle behind FastICA is that the fast fixed-point iterative algorithm find projections that maximize the non-Gaussianity of components by their kurtosis (the fourth-order cumulant given to a random variable). In simpler terms, as kurtosis is identically zero for Gaussian distributed signals, the objective is to maximize the magnitude of the kurtosis to make the estimated sources as non-Gaussian (i.e. as independent) as possible. The kurtosis that is used to describe the peakedness of a distribution is defined as

$$kurt(x) = E\{x^4\} - 3(E\{x^2\})^2 \quad (7)$$

for a zero-mean random variable  $x$ . Further details about the FastICA algorithm can be found in (Hyvärinen and Oja, 1997; James and Hesse, 2005).

## Dataset

An annotated and validated database is very important for the study of ECG signal processing and pattern recognition in general, and such a "standard" database is particularly useful in this study. This allows for the validation of the newly developed algorithms and comparison with the results from others work. We have selected the MIT-BIH database because it is completely annotated by medical specialists and arguably the most popular one used by many other authors and quoted in numerous important

publications in this field e.g ( Belgacem et al., 2003; Chou and Yu, 2008; Jiang et al., 2006; Moody et al., 2001; Wang et al., 2012). The associated noise recordings in the dataset were made using physically active volunteers. Standard ECG recorders, leads, and electrodes were used; of which the electrodes were placed on the limbs in positions where the subjects' ECGs were virtually invisible. Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as they can be noise of other types (Moody et al., 1984).

### Proposed Method

ICA based blind source separation techniques could be used to separate ECG and ambulatory noise, as these signals are uncorrelated (Castells et al., 2005; Hyvärinen and Oja, 2000). To successfully apply ICA blind source separation, we need multi-lead ECG recording and the ECG and noise to be removed should be independent each other. We try to investigate the application of ICA for separation of electrode motion artifact using just two signals, ECG from modified lead II taken from MIT-BIH dataset, electrode motion noise from MIT noise stress test database.

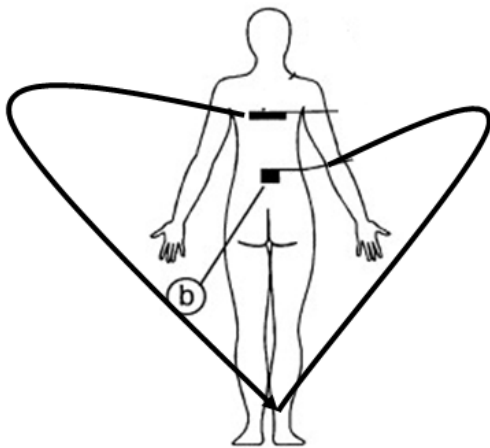


FIG. 4 (Romero, 2011) SETUP FOR MOTION ARTIFACT REMOVAL, LEAD (B) IS PLACED AT LUMBAR CURVE WHERE ECG SIGNAL IS MINIMAL.

For practical purpose, lumbar curve height does have minimal ECG so electrode at that point captures maximum noise,(Romero, 2011). In his work, proposed 8 channel noise recording to separate the 'em' noise however during certain first aid emergency situation, this process is long.

But it was suggested that the noise recorded at the lumbar region may not be the same as the front lead motion artifact. To test our methods, we selected MIT-

BIH Noise Stress Test Database. The signal mixture was prepared by mixing pure ECG from MIT-BIH record with varied amount of SNR, so that we can test the algorithm feasibility over wide range of noise level. For practical application, placement of electrode on the limb area where ECG is minimal will serve the purpose, and lots of such point exists(Moody et al., 1984) , our discussion was limited to the capacity of ICA to separate the 'em' noise for ambulatory ECG.

$$\text{observed signal} = \text{ECG} + \theta N \quad (8)$$

where N is motion induced noise in the ECG signals in general, although other types of noise like base line wander and power frequency interference if present can be easily removed by adaptive filter ((He et al., 2006). 'em' noise is difficult to be removed with conventional filter since it takes the shape of original signal hence it is difficult to be identified.

'em' noise data set was also obtained from MIT-BIH Noise Stress Test Data base. 'em' artifact was mixed with pure ECG with various SNR for more extensive testing of our approach. The equation for mixing two signals can be given as

$$\begin{aligned} \text{Modified Lead II} &= S1 + N' \\ \text{Limb Electrode} &= S2 + N'' \end{aligned} \quad (9)$$

Where modified lead II records ECG signal and part of electrode motion noise, the limb electrode also measures ECG signal and electrode motion noise but ECG is minimal in this part, so majority of limb electrode signal is composed of 'em' noise.

FastICA algorithm was used to separate the pure ECG and Motion artifacts.

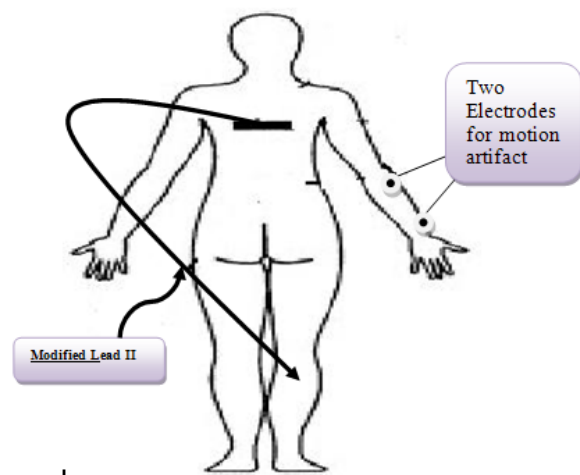


FIG. 5 PROPOSED SETUP FOR MOTION ARTIFACT REMOVAL; TWO ELECTRODES ARE USED TO RECORD MOTION ARTIFACT

With two independent components separated out from the ICA algorithm, one has to determine which one is the ECG. Visual inspection is certainly not desirable. In practice, the separated components tend to have more

distinctive properties than the original signals both in time and frequency domains. Hence, the statistical properties of these waveforms were employed and recognized automatically using kurtosis. The kurtosis is the fourth-order cumulant as explained in equation (7). The kurtosis is zero for Gaussian densities. For continuous noise, the kurtosis value is much smaller compared with that of normal ECG. In our work, a threshold of 5 is selected as cutoff, a component whose modulus of kurtosis is below this threshold will be considered as continuous noise. The main reason for choosing kurtosis is its simplicity. Computationally, kurtosis can be estimated by using the fourth moment of the sample data.

### Classification

After the separation of pure ECG and motion related artifacts, the ECG segments were classified into normal and abnormal ones in order to compare with the results from classification performed on noisy ECG signals and pure ECG signals extracted by the ICA. Since the MIT-BIH dataset is completely annotated, the occurrence of R peak and most of the diagnostic information of the ECG signals is known. We selected portion on both side of R peak. 200 data points were taken in each sample which is about 0.556 s in terms of sampling interval. The sampling frequency for this signal is 360 Hz. The extracted samples of 200 data point have all the required information of ECG pulse including P and T wave as well, which gives us complete information contained in single pulse including the cases of noise presence along with the original signal.

With the annotated beats information provided with the dataset, two datasets of normal and Right bundle branch block arrhythmia were selected, each of which consisted of about 100 beats of each type. One dataset was used for training and other for testing. Classification was done using Back Propagation neural network (BPNN) implemented on MATLAB software. ANN is widely used classifier for ECG (Al-Fahoum and Howitt, 1999; Belgacem et al., 2003; Castillo et al., 2012; Chikh et al., 2003; Chou and Yu, 2008; Jiang et al., 2006; Wang et al., 2012). Back-propagation neural network (BPNN) used in this study is a three-layer feed-forward structure (Jang et al., 1997), of which the first layer is the input layer that has the ICA features as inputs; while the second layer, also called the hidden layer, has 20 neurons and the output layer has two neurons, which is equal to the number of ECG beat types to be classified. In this study, the hyperbolic

tangent functions are used in the first and second layers, and the identity function is used in the output layer. The weight and bias values in the BPNN are updated by Levenberg-Marquardt optimization method (Jang et al., 1997) with a learning rate of 0.1. A criterion of 0.01 in mean-square-error is empirically determined to terminate the iterations in the training phase of the classifier. Time taken for the training of classification was about 1.2 s in the Matlab computing environment based on the average over 10 times.

### Experiments and Results

Matlab software was used for the signal processing, pattern recognition, visualization and user interface in this study. The ICA BSS algorithm used was the FastICA which has shown to best removal noise in this application (Sarfraz et al., 2011).

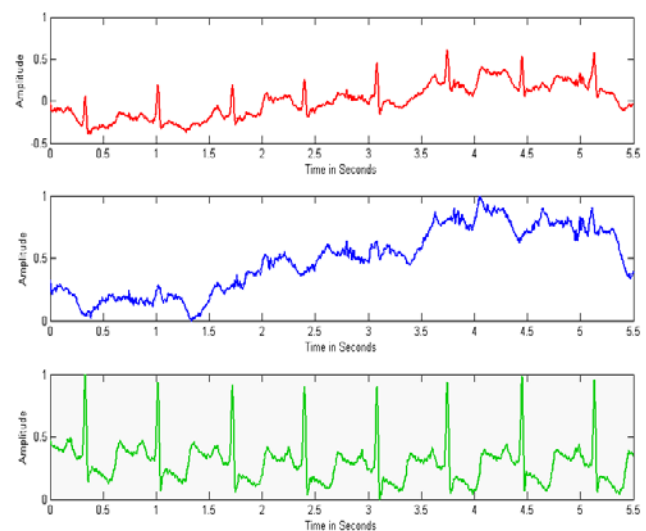


FIG. 6 PART OF ECG COMBINE WITH NOISE -06DB (TOP PANEL), 'EM' NOISE MIDDLE PANEL, EXTRACTED ECG WITH ICA BOTTOM PANEL. Y AXIS IS NORMALIZED AFTER ICA

To test the effectiveness of the ICA in the removal of motion related artifacts, ANN classifiers for normal and abnormal ECGs with and without an ICA pre-processing stage were experimented with. ECGs mixed with motion related noise at a variety of signal to noise ratios ranging from 24 dB to -12 dB were used to validate the proposed method. The sensitivity of a test is defined as the proportion of people with arrhythmia who will have a positive result. The specificity of a test is the proportion of people with normal ECG who will have a negative result. Higher value of specificity and sensitivity indicate better classification and small error. Comparison results shown in Table 1&2 and Fig. 7&8 have clearly indicated that when the signal to noise decreased, the ANN only classification without using ICA degraded significantly by lowering recognition

accuracy. With the significant improvement of the ICA de-noising recognition accuracy in poor signal to noise ratio conditions, it is observed from the results that ICA noise removal improved the accuracy of the classification, while in noisy ECG there was improvement up to 40% in sensitivity and 20% in specificity.

TABLE 1 COMPARISON OF CLASSIFICATION SENSITIVITY BEFORE AND AFTER SOURCE SEPARATION.

Parameters	(%)-12(dB)	(%)-6 (dB)	(%) 0.1 (dB)	(%) 6 (dB)	(%) 12 (dB)	(%) 24 (dB)
Sensitivity (Before)	58.3	60.1	81.6	82.9	90.7	97.1
Sensitivity (After)	93.7	95.6	96.5	97.1	97.7	98.4

TABLE 2 COMPARISON OF CLASSIFICATION SPECIFITY BEFORE AND AFTER SOURCE SEPARATION.

Parameters	(%)-12(dB)	(%)-6 (dB)	(%) 0.1 (dB)	(%) 6 (dB)	(%) 12 (dB)	(%) 24 (dB)
Specifity (Before)	48.6	62	73	85.2	95.9	96
Specifity (After)	60	71.4	76.3	88.1	96.7	98.1

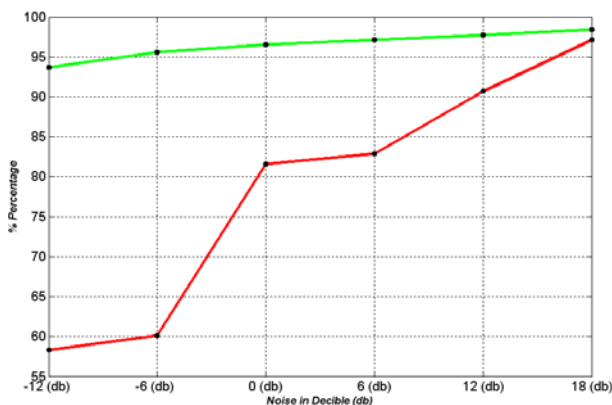


FIG. 7 RELATION BETWEEN SENSITIVITY OF CLASSIFICATION ALGORITHM WITH AND WITHOUT ICA

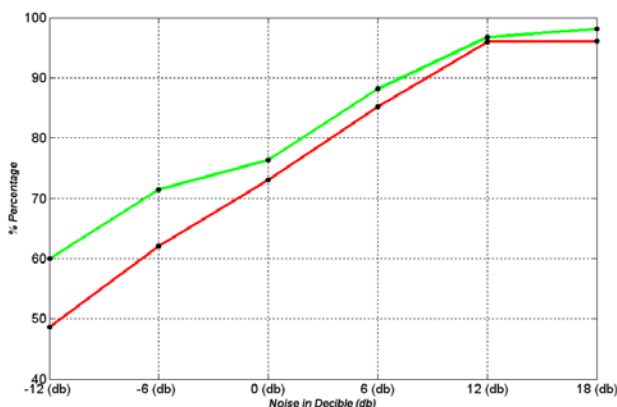


FIG. 8 RELATION BETWEEN SPECIFITY OF CLASSIFICATION ALGORITHM WITH AND WITHOUT ICA

## Discussion

This work has shown that ICA can effectively remove

motion induced artifacts in ECG signals, thus improving the accuracy automatic ECG recognition systems. The method developed in this study has potential applications to sports related ECGs, first aid emergency and Holster monitoring and other ambulatory EEGs in which motion related noise is no trivial. Prerecorded data were used in the study, but they were recorded from patients and healthy subjects and therefore valid real data. The assumption made in the work is that noise signal conducted by human bodies is a linear attenuation of its source. This appears to be the general assumption adopted in ECG, EMG and many others. Even if there is minor changes in the phase of signals (i.e. delays) they should be negligible since ECG signals are generally slow changing, low frequency ones.

## Conclusions

This paper has proposed the use of the ICA as a pre-processing stage to eliminate motion induced artifacts in ECG signals and the combined use of the ICA and ANN to achieve significant improvement of accuracy of automated recognition in the presence of non-trivial noise of such nature. There are many methods to perform ICA and ECG pattern recognition, and it will be interesting to identify the optimal combination to achieve best results, which is left for future work.

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